Model Predictive Control Based Safe Battery Charging for LFP ($LiFePO_4$) Batteries

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1. Abstract

In the industry, simple algorithms are used for charging batteries. CC (Constant Current), CV (Constant Voltage), CVCC (Constant Voltage Constant Current). These are simple and have less computational cost, but are not optimal for battery health. When batteries are charged or discharged, batteries degrade, and this degradation is boosted under high temperature and high current. In this project, an MPC algorithm is used to seek the optimal charging sequence monitoring the factors that cause degradation in batteries. How we designed our MPC controller to improve safety and battery health while charging or discharging is based on four major factors: Ambient Temperature, Core Temperature, Surface Temperature, and Current. We know that the rate of battery degradation is strongly linked to the value of temperature. Additionally, higher current flow throughout the system causes battery degradation. Also, understanding that an increase in temperature brings more negative effects on the battery's health as compared to an increase in current. Considering all these factors we can create an MPC that is better than the current simple algorithms available.

2. Introduction

Battery usage has increased dramatically due to the development of mobile devices, electric cars, and computers. To enhance productivity and convenience, fast charging becomes a major topic. However, a lack of control towards fast charging and charging methods causes a significant reduction of battery lifespan. Additionally, as the battery is being charged, the battery could heat up to dangerous levels and therefore result in serious fire hazards.

The purpose of this study is to design an MPC controller for the ECM (Equivalent Circuit Model) battery to optimize the charging sequence instead of traditional charging. Under high temperatures or when overcharge occurs, the battery exceeds the safety operation boundary. When this occurs the battery has a chance to light in a self-sustained fire resulting from a thermal runaway. In order to avoid the side reactions that compromise battery life and its safe operation, applying MPC can avoid these potential hazards by evaluating what are the system constraints and then applying them to the controller.

Having knowledge of SOC(State of capacity) allows damage prevention, safety insurance, minimal charge time, and maximal battery life. The battery will be less likely to result in thermal runaway and slow down the declination of the SOH(State of health). The optimal charging profile is applied over a moving horizon following a modified MPC approach and is implemented in the Pyomo Python Library. The optimized temperature will significantly reduce battery degradation and maximize battery life. When the study was initiated, the SOH (state of health) was being considered. However, the equation related to the state of health is non-linear and is arbitrarily small for Pyomo to compute in the range of e^{-100}, resulting in not including SOH in our calculations due to the complexity. This paper focuses on the optimization of charging and discharging rate with temperature and current that relates to SOH while applying different ambient temperatures.

3. Dynamics Model Description

Batteries can be represented with Equivalent Circuit Models (ECM) for simplicity. A 2-RC model for a $LiFePO_4$ battery is used in this project which has three states: state of charge (SOC), diffusion voltage 1 (V_1), and diffusion voltage 2 (V_2) [1]. The schematic of the 2-RC ECM model is shown in Figure 3-1.

A lumped thermal model is used to relate the thermal characteristics of the battery and the ambient temperature. The lumped thermal model has two states: core temperature (Tc) and surface temperature (Ts) of the battery. Surface temperature is affected by both the ambient temperature and core temperature. The schematic of the lumped thermal model is shown in Figure 3-2.

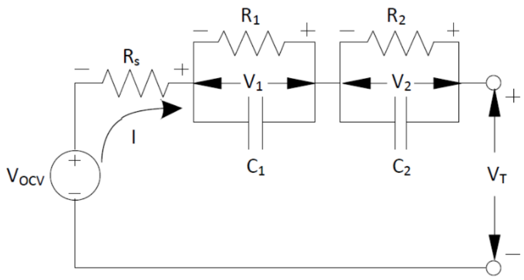

Figure 3-1. Schematic of 2-RC ECM battery model [1]

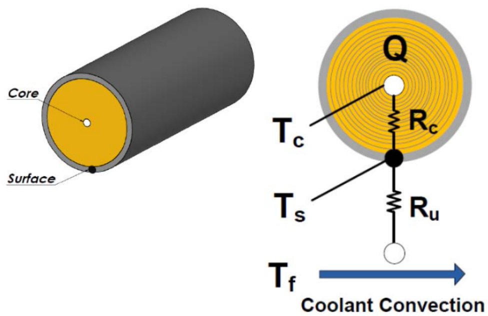

Figure 3-2. Schematic of Lumped Thermal Model [1]

The dynamics equations of the 2-RC ECM and lumped thermal models are given by:

Dynamics Equations From 2-RC ECM:

$$\frac{d}{dt}SOC(t) = \frac{I(t)}{C_{battery}} \tag{1}$$

$$\frac{d}{dt}V_1(t) = -\frac{1}{R_1C_1}V_1(t) + \frac{1}{C_1}I(t) \tag{2}$$

$$\frac{d}{dt}V_2(t) = -\frac{1}{R_2C_2}V_2(t) + \frac{1}{C_2}I(t) \tag{3}$$

Dynamics Equations From Lumped Thermal Model:

$$\frac{d}{dt}T_C(t) = \frac{1}{R_CC_C}\left(T_s(t) - T_C(t)\right) + \frac{1}{C_C}\left|Q(t)\right| \tag{4}$$

$$\frac{d}{dt}T_s(t) = \frac{1}{R_uC_s}\left(T_f(t) - T_s(t)\right) + \frac{1}{R_uC_s}\left(T_s(t) - T_C(t)\right) \tag{5}$$

where:

$$Q(t) = I(t)\left(OCV\left(SOC(t) - V_T(t)\right)\right) \tag{6}$$

$$OCV\left(SOC(t)\right) = p_0 + p_1SOC(t) + p_2SOC^2(t) + p_3SOC^3(t) \tag{7}$$

$$V_T(t) = OCV\left(SOC(t)\right) - V_1(t) - V_2(t) - I(t)R_s \tag{8}$$

The input current *I(t)* is the control variable where the positive sign denotes charging and the negative sign denotes discharging case. C_{bat} is the battery charge capacity that represents the amount of charge the battery can hold. R_1, C_1, R_2, C_2, R_0 are parameters to describe the diffusion voltage in the battery. It is assumed that the lumped thermal model of the battery follows longitudinal homogeneity, [4] and R_c, C_c, R_u, and C_s represent the core thermal conduction resistance, core thermal capacity, surface thermal convection resistance, and surface thermal capacity, respectively. $Q(t)$ is the heat generated from the core during the charging/discharging process. $OCV(t)$ and $V_T(t)$ are the open-circuit voltage and the output voltage, respectively. All battery parameters are in general a function of temperature. However, in this project, they are considered to be constants for simplicity and purpose. All parameter values are listed in table 3-1. [1]

$C_{bat}(Ah)$	$R_1(Ohm)$	$C_1\ (F)$	$R_2(Ohm)$	$C_2\ (F)$
2.3	0.0123	2575.7	0.0149	84450
$R_0\ (Ohm)$	$R_C(\frac{K}{W})$	$C_c(\frac{J}{K})$	$R_u(\frac{K}{W})$	$C_s(\frac{J}{K})$
0.0088	1.94	62.7	3.19	4.5
p_0	p_1	p_2	p_3	
3.4707	1.6112	−2.6287	1.7175	

Table. 3-1 Parameters for the 2-RC-Thermal Battery Model

4. MPC Formulation

The study of the report only utilizes the optimal temperature as the control target of MPC. CFTOC (Constrained Finite Time-Optimal Control) is formulated as given below:

$$\min_{z(0),\dots,z(N),u(0),\dots,u(k)} \sum_{k=0}^{N} P\left(z_0 - z_f\right)^2 + z^T(k)Qz(k) + Ru^2(k) \tag{9}$$

subject to:

$$z(k+1) = z(k) + \Delta t * f(z(k), u(k))$$

$$z_{min} \le z(k) \le z_{max}$$

$$u_{min} \le u(k) \le u_{max}$$

$$z_0(N) = z_f$$

The core temperature $\frac{d}{dt}Tc(t)$ of the battery cell is a function that consists of nonlinear terms. In order to avoid the main side reactions that compromise battery life and its safety, the battery should be restricted through constraints. The constraints are nonlinear in general, and they might result in nonconvex solutions;

however, the solution space can be convexified with more conservative linear constraints.

The dynamics states and the input control from the previous part are notated as below in CFTOC.

$$z = \begin{bmatrix} z_0 \\ z_1 \\ z_2 \\ z_3 \\ z_4 \end{bmatrix} = \begin{bmatrix} SOC \\ V_1 \\ V_2 \\ T_c \\ T_s \end{bmatrix} \qquad u = [u_0] = [I]$$

For the calculation of CFTOC, all dynamics equations (1) - (8) are discretized by means of the First-Order Euler Discretization method.

The state constraints, z_{min}, z_{max}, u_{min}, u_{max} , are chosen based on real-world applications. Charging and discharging batteries to a substantially high or low SOC may damage the battery. V1 and V2 are mostly determined based on the battery dynamics, and they don't play an important role in this problem. Therefore, a wide range of V1 and V2 is given. Tc and Ts are expected to reside within a moderate temperature range to minimize degradation of the battery. Mostly, a temperature above 45℃ is fatal to the battery life. However, we leave some margin on the upper bound for Tc and Ts for more flexible operation.

$$z_{min} = \begin{bmatrix} 0.2 \\ -200 \\ -200 \\ 15 \\ 15 \end{bmatrix} \qquad z_{max} = \begin{bmatrix} 0.9 \\ 200 \\ 200 \\ 55 \\ 55 \end{bmatrix}$$

$$u_{min} = [-35] \qquad u_{max} = [35]$$

The initial states and final states are assigned as below. We start charging the battery with the initial SOC at 0.2. V1 and V2 are typically very low. So, 0 is a good initial state for both. The initial states of Tc and Ts are selected considering thermal equilibrium with the surroundings where Tf is the ambient temperature. For the final states, only SOC is considered in this MPC problem since we are interested in charging the battery up to 0.6 SOC. Therefore, all the other final states are neglected.

$$z_{init} = [0.2, 0, 0, T_f, T_f]$$

$$z_f = [0.6, -, -, -, -]$$

The cost function (9) is composed of three parts. The first term in the cost function minimizes the difference between the current SOC and the final SOC at all time steps. Therefore, the rate of charging the battery can be determined through the first term. The second term is in the general quadratic function form, and it is used to minimize only the core and surface temperatures because SOC, V1, V2 are not minimization targets in this problem. The input appears in the third term of the cost function. In this model, there is only one input which is the current flowing into the battery.

In this experiment, it is desired to keep the battery's core and surface temperatures low during the charging process to prevent degradation of the battery. The current is also one factor that shortens the battery life, so it needs to be kept low as well. However, the battery needs to be charged to achieve the goal of this MPC problem, so the current cannot be absurdly low. Additionally, high core/surface temperatures accelerate battery degradation more than the current does. Therefore, higher weights (Q) are assigned to the temperatures than the current (R). The battery charging rate (P) in the first term of the cost function can be assigned by the user's preference.

The weighting factors are assigned as shown below:

$$P = 10$$

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 100 & 0 \\ 0 & 0 & 0 & 0 & 100 \end{bmatrix}$$

R = 1

Timestep, horizon size *N*, and total simulation length *M* are selected considering both the simulation time and accuracy of the MPC model.

$$\Delta t = 5 \qquad N = 50 \qquad M = 500$$

5. Results

Eight experiments were conducted to see the response of the battery to different ambient temperatures (Tf) during charging with the MPC algorithm. The first four Tf trends (Tf_1, Tf_2, Tf_3, Tf_4) are designed to see the general response of the battery MPC model to different constant ambient temperatures (Tf). The next four Tf trends (Tf_5, Tf_6, Tf_7, Tf_8) are designed to observe battery MPC model responsiveness to rapidly varying ambient temperature (Tf).

Tf_1: Constant temperature at 15℃
Tf_2: Constant temperature at 25℃
Tf_3: Constant temperature at 35℃
Tf_4: Constant temperature at 45℃
Tf_5: Gradual increase from 25℃ to 45℃
Tf_6: Gradual increase from 25℃ to 45℃, and decreasing from 45℃ to 25℃
Tf_7: Gradual increase from 25℃ to 45℃, drop back to 25℃, and repeat
Tf_8: Average at 30 with 5℃ variance

In the figures below, the ambient temperatures are represented as dashed lines.

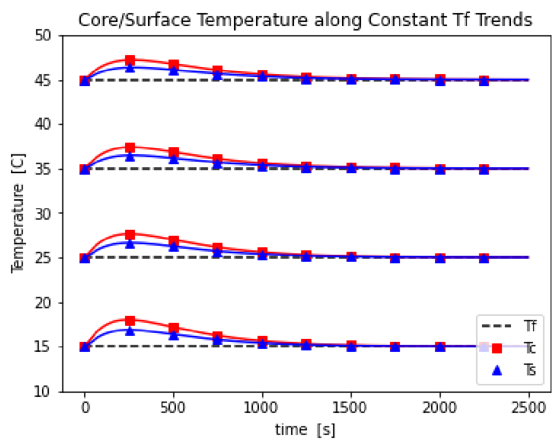

Figure 5-1

For all constant ambient temperatures, as we increase the current, the core and surface temperatures of the battery increase, the core temperature being higher since that is where the heat is being generated. However, as the current decreases as a function of time and as a result of heat transfer from the core to the ambient, the temperature of the core will decrease until an equal steady-state temperature is reached for the core, surface, and ambient. For all time the ambient is cooling the temperature of the battery until the battery reaches the same temperature as the ambient air.

Based on the temperature trends in the initial phase when there is a high current, it can be understood that at higher ambient temperatures the difference between the core and surface temperatures is less, meaning that there is less heat transfer at higher ambient temperatures in the beginning.

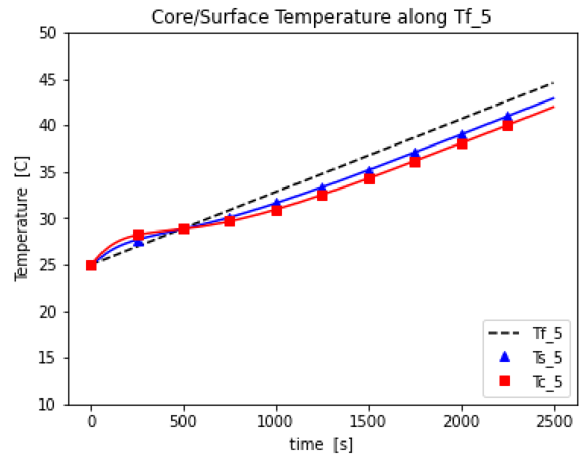

Figure 5-2

Initially, due to the high current at the beginning of the experiment, the core temperature is greater than the ambient temperature and thus there is heat transfer from the core to the surface to the ambient. However, as the current decreases, the heat generated at the core of the battery drops below that of the ambient and thus the direction of heat transfer is reversed and now the heat is transferred from the ambient to the core. Initially, the ambient is cooling the battery, but then the ambient starts to heat the battery.

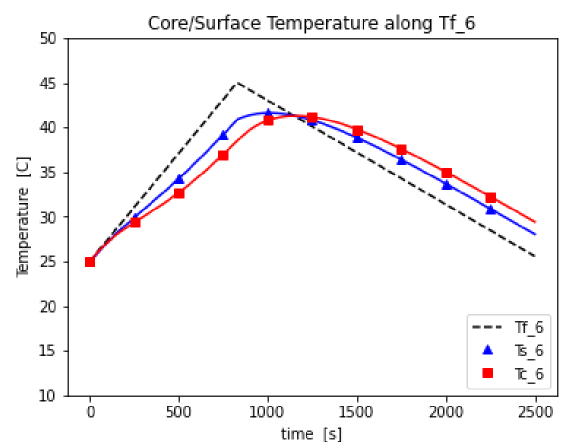

Figure 5-3

As the ambient temperature is increasing the ambient air is heating the battery, and when the ambient temperature is decreasing, it is cooling the battery. The initial rate of increase of ambient temperature is high enough that even though there is heat generation due to high current in the core, it is still below that of the ambient. Also, the ambient temperature is initially heating the system more than the high current is, which is why the surface temperature is initially higher than the core temperature.

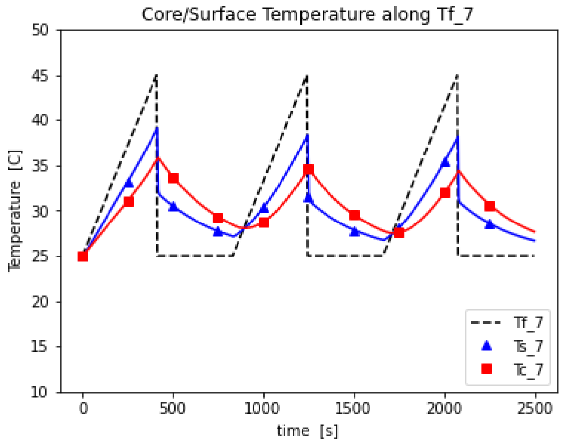

Figure 5-4

As the ambient temperature is increasing the ambient air is heating the battery, and when the ambient temperature is decreasing the ambient air is cooling the battery. Since the trends for the blue and red curves look the same at each of the three intervals, it can be seen that the heat generation due to current is not playing a significant role in the change in temperature of the battery, compared to the effects of that of the ambient on the temperature, even during the initial phase where there is high current. Since in the beginning, the temperature of the surface is higher than that of the core, it means that heat generation due to the ambient is much larger than the heat generation of the high current.

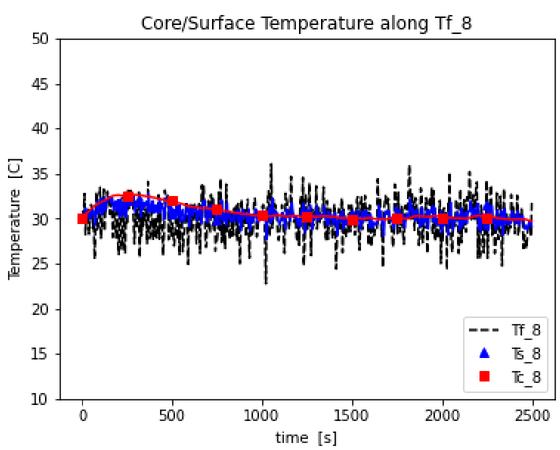

Figure 5-5

The ambient temperature was set at an average temperature of 30℃ with a 5℃ variation. We wanted to observe the behavior of the system when there either exists a fluctuation in ambient temperature or the ambient temperature measurement is noisy. We observe that the behavior of T_S and T_c are similar to that of Figure 1 when the ambient temperature was constant except that the T_S and T_c are fluctuating also. The average of T_S and T_c both initially rise above 30℃, then decrease and level of to 30℃.

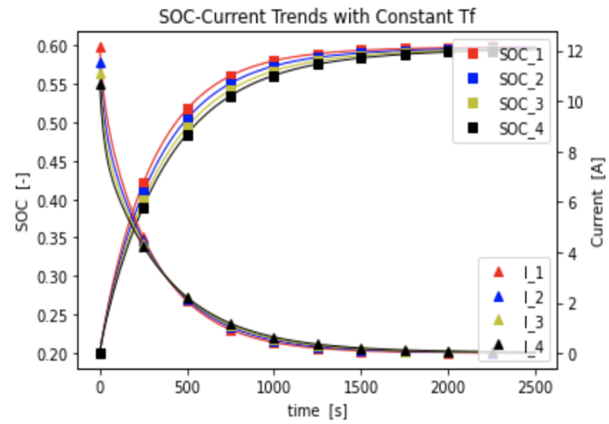

Figure 5-6

From Figure 5-6, it can be seen that for constant ambient temperatures, as we increase the ambient air temperature, the batteries get charged more slowly since at each time step the SOC is lower for higher T_f values. The MPC realizes the lower temperature and then a higher current is applied to the system by making the charging process quicker. The overall current is exponentially decreasing as a function of time. Initially, the currents for the lower T_f case are higher, but after a certain time, the currents for the higher T_f tend to be larger. The battery MPC model is adjusting the amount of current given to the system based on the ambient temperature. As shown in Figure 5-6, the lower the ambient temperature is, the higher the current is applied by the MPC algorithm.

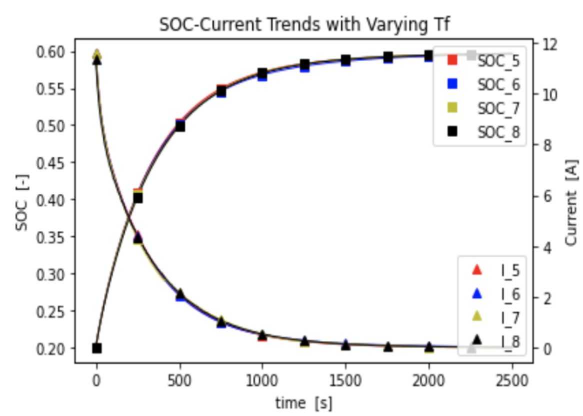

Figure 5-7

In Figure 5-7, the SOC plots appear not to be affected much by the fluctuations from different ambient temperatures. We conclude that the MPC model mostly applies itself to an average temperature of the fluctuating

T_f which results in our plot. We want the SOC to go to 0.60, after a certain time of about 1000s, the rate of increase of SOC can decrease since there is plenty of time left for the SOC to reach its desired goal with a low rate of increase. The overall current is exponentially decreasing as a function of time observed in Figure 5-7. Bigger fluctuations are not observed in Figure 5-9 due to the similar average ambient temperatures during different cases.

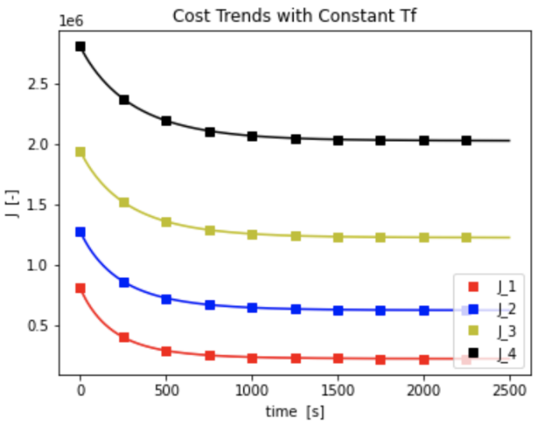

Figure 5-8

The general trends of MPC cost with constant Tfs are shown in Figure 5-8 above. The costs monotonically decrease as time increases. It proves that our 2-RC ECM-thermal battery model is asymptotically stable, and the infinite horizon cost is a Lyapunov function for the system.

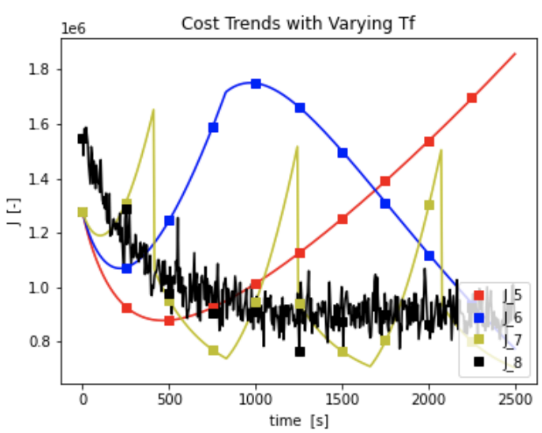

Figure 5-9

However, when varying T_f takes place in the system as a disturbance, the system becomes not asymptotically stable because the varying T_f plays a role as an undesired input that the system cannot really control. Becoming an unstable system is shown in Figure 5-9. The cost of MPC is not monotonically decreasing anymore, and they move along the varying Tf trends, which means the stability of the system highly depends on the disturbance Tf.

6. Conclusion

The fast and safe charge of lithium-ion batteries is an open problem. In this experiment, we physically controlled the ambient temperature, however, the ambient temperature in real life is unknown. Thus if only a single optimization was used for the simulation, the unexpected changes in the ambient temperature wouldn't have been considered since it is not part of our model and is acting sort of as a disturbance. This could result in many issues such as battery temperature skyrocketing and exploding which is from thermal runaway. However, since we are using MPC, the battery model is handling the changes in the ambient temperature well because we can respond to the new temperatures and thus optimize accordingly, as seen from the figures above.

For future improvements to this MPC problem, we can set the ambient temperature as one of our decision variables. Therefore, the inputs will be Tf(t) & I(t). We would give a certain temperature range to the battery, and then control the cooling system (Tf) and current (I) for optimal charging, considering the health status of the battery.

Another improvement we can do is to linearize our system. We can achieve this by applying certain mathematical maneuvers that we can obtain through other research papers about linearization on nonlinear models. This can allow us to input more complex nonlinear equations such as the state of health by linearizing them.

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